

# Data Panel Regression Implementation for Predicting Divorce in Regencies and Cities of West Java Province

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## Article Info

### Article history:

Received September 10, 2026

Revised September 30, 2026

Accepted September 30, 2026

Published October 15, 2026

## ABSTRACT

Family is an important component in a community. Divorce, as a major indicator of a family, is used as a metric to gauge family health in a community. A Prediction of the total number of divorces for regency/city in West Java Province was developed. Three models are used for prediction and compared to each other through MAPE, MAE, and RMSE tests, with an additional classic assumption test and model selection test for additional guidance. The models are the common effects model, fixed effects model, and random effects model. The first iteration of prediction has a best MAPE of 33.25%, achieved by the common effects model, and it violated nearly all classic assumption tests. A log transformation for the features was conducted. In this iteration of prediction, the random effects model has the best MAPE with 19.95% and no major assumption test violations. It has an RMSE of 1550.66 and MAE of 1002.35. In addition, during this study, an entry has a completely missing divorce value for the entire training dataset. An attempt at zero-shot was conducted; the first iteration had 73.5% MAPE, and the second iteration had a MAPE of 5.3%, a significant improvement from log transformation. For further study, an analysis could be made to determine what the common denominator is between city/regency that has low MAPE. Through this analysis, an adjustment could be made for the model to improve predictive ability. Additionally, new data could be introduced to the model.

**Keywords:** Divorce; MAPE; Prediction.

## INTRODUCTION

Family is the main foundation of a society; it is the cornerstone upon which society stands [1]. Without it, a society cannot exist and function. This cornerstone of a society is the smallest community an individual can build. It is from a family that a family ward (RT/RW) can be built. From this group, another community can be built to become a village. Afterward, it becomes a sub-district, then cities and regencies, then provinces; then, with these components, a nation can be built.

A healthy family is of utmost importance for a community, be it a small community or a big community such as a nation. The reasoning underlying this is that a family affects economic productivity, psychological and physical health, and the growth of the next generation. Families are central to cultivating core entrepreneurial values such as perseverance, discipline, and leadership, which

contribute to improved household welfare and community resilience [2]. To know about familial health in a community, the number of divorces is one of the metrics that can be used.

Added on from Islamic teachings, family is a blessing for a living being, especially humans. From which an individual can feel love and affection for one another. This is mentioned in Q.S. Ar-Rum:21: "And one of His signs is that He created for you spouses from among yourselves so that you may find comfort in them. And He has placed between you compassion and mercy. Surely in this are signs for people who reflect."

Not limited to that, one hadith mentions how great a thing divorce is. Which said the following: "Jabir reported that Allah's Messenger (ﷺ) said: Iblis places his throne upon water; he then sends detachments (for creating dissension) ; the nearer to him in rank are those who are most notorious in creating dissension. One of them comes and says: "I did so and so." And he says: "You have done nothing." Then one amongst them comes and says: "I did not spare so and so until I sowed the seed of discord between a husband and a wife." The Satan goes near him and says: "You have done well." A'mash said: He then embraces him." (Sahih Muslim 2813b).

Connecting ourselves with the current era, science, more specifically data science, has progressed to the point that we can infer which factors contribute to divorce numbers and how much they influence it. Data science can be explained as a process where large volumes of data are organized and interpreted to extract practical insights [3]. Perhaps the best way to think about data science is as a process that takes data and generates insight and prediction from it [4]. With data science as the foundation, data consisting of the number of divorces and Islamic marriages from regencies and cities in West Java province from 2018 to 2025, and additional data such as average monthly per capita expenditure, total population, population growth, population density, and gender ratio can be used to predict the number of divorces or to know what contribution something makes to a divorce.

Panel data regression is the method that will be used in this study. Regression analysis examines the relationship between a dependent variable (explained variable) and one or more independent variables (explanatory variables), acknowledging that the relationship is inherently uncertain and imperfect [5]. Panel data regression is a combination of cross-section data and time-series data, where the same cross-section unit is measured at different times [6]. The panel dimension also offers an additional advantage for forecasting purposes. Which is to allow the model to exploit cross-sectional dependence among West Java's cities and regencies. Fosten and Nandi [7] demonstrate that when units share common factors—such as provincial economic conditions or policy shocks—modeling this dependence through multifactor error structures improves out-of-sample prediction accuracy. Furthermore, they find that pooling coefficients across units performs better than a simple time-series benchmark when the time dimension is short, which aligns with the 2018–2025 observation window. The method is well-suited to process data on divorce numbers, Islamic marriages, average monthly per capita expenditure, total population, population growth, population density, and gender ratio from cities and regencies in West Java Province, 2018-2025.

The analysis takes place in West Java Province for the following reason, highest population in Indonesia, with a total population of 50,342.5 thousand people. Analysis that is being done in this province has the potential to make a significant influence. Knowing population health from divorce numbers will provide a tool for related authorities to make a suitable policy that fits with its population.

## METHOD

This study uses the Cross-Industry Standard Process for Data Mining (CRISP-DM) as the core framework for developing and evaluating the machine learning model. CRISP-DM is a six-step process, which are: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. The ability to provide a systematic approach for the study is the reason behind choosing CRISP-DM as the framework. Another reason is that its continued relevance and application in modern data analysis projects, including the comparison of different methodologies, have been well-documented [8]. Figure 1, it illustrates how each CRISP-DM stage is implemented.

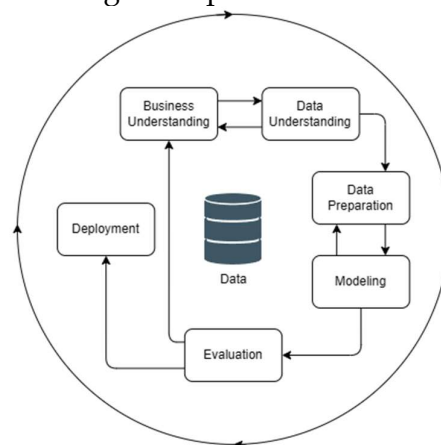


Figure 1. CRISP-DM

Source : F. Martínez-Plumed et al. [9]

### Business Understanding

In this study, the problem is the need to evaluate family health in a community. To achieve the mentioned goal, this will be done by analysing the divorce rate, as divorce is one of the metrics to check familial health in a community. The aforementioned analysis is done by predicting the divorce rate and how other factors affect divorce. By leveraging divorce prediction, an assessment of social health in a community can be conducted. Enabling a timely implementation or a remedial intervention, as appropriate. Furthermore, insights into the key determinants of divorce provide an additional analytical framework for policy consideration.

### Data Understanding

The data understanding phase revolves around collecting, describing, and exploring the data required for the study. This research uses data that are collected

from the Badan Pusat Statistik (BPS) of West Java Province. All the datasets are under the following main category: Statistics of Demography and Social.

The first dataset used in this study is entitled “Marriage and Divorce by City/Regency in West Java Province, 2018-2025”, which contains statistical data on marriage and divorce occurrences across regencies and municipalities in West Java Province. The dataset was obtained from the official BPS West Java statistical database under the Population and Migration category. Four data points were found in this dataset: marriage numbers, divorces initiated by husband, divorces initiated by wife, and total number of divorces. Each city and regency under West Java Province has an entry, totaling 27 cities and regencies, with an additional row for a summary of all cities and regencies. Two cities are missing an entry: Pangandaran is missing the total number of divorces from 2018-2024, and Bandung Barat is missing one data point for the year 2018 on the total number of divorces. This dataset only tracks Islamic marriages.

The second dataset used is titled “Population, Population Growth, Population Percentage Distribution, Population Density, Gender Ratio by City/Regency in West Java Province, 2018-2025”. This dataset was obtained under the Population and Migration category. It has six variables, which are: name of regency/city, total population (in thousands), annual population growth rate, population percentage, population density (persons per square kilometer), and gender ratio. All data are complete, with no missing values for any entry. This dataset has 27 observational regency/city.

The last dataset used is titled “Percentage of Monthly Per Capita Expenditure on Food and Non-Food Items in Urban and Rural Areas by Regency/City in West Java Province, 2018-2025”. This dataset falls under the Consumption and Income category and has four columns. Name of regency/city, Average monthly per capita expenditure on food (in Rupiah), Average monthly per capita expenditure on non-food items (in Rupiah), and Total average monthly per capita expenditure (in Rupiah). No missing values are found in this dataset.

The collected data were initially examined to identify the structure and characteristics of the dataset, including the geographical unit, variables, and statistical values. The purpose of this initial analysis was conducted to ascertain the suitability of the dataset and to identify potential data quality issues that might need to be addressed during the Data Preparation phase.

### **Data Preparation**

The Data Preparation phase aims to transform the raw data into a suitable dataset for model development. This phase includes data cleaning, handling missing and duplicate data, removing irrelevant information, data transformation, and feature preparation. The purpose of this phase is to have a clean and structured dataset for modeling processes.

All collected datasets are merged into one dataset. In the process, column names are organized, duplicate entries are removed (i.e., city and regency names are duplicated three times from three different datasets), the West Java summary is removed, relevant data are adjusted to fit the correct town and year, feature

selection is performed, training and validation data are separated (2018-2024) and validation data (2025), and missing data are handled.

The finalized features are as follows: marriage, divorce total, average spending total, population, population growth, population density, and gender ratio. Some features are excluded from the model for various reasons; average spending on food and average spending on non-food are removed because of perfect collinearity with spending total, divorce initiated by husband and divorce initiated by wife are excluded because of perfect collinearity with divorce total, and population percentage is excluded by virtue of missing metadata for explaining said data.

**Table 1. Dataset Structure**

| Dataset    | Units               | Period    | Observations | Variables |
|------------|---------------------|-----------|--------------|-----------|
| Training   | 27 cities/regencies | 2018-2024 | 189          | 7         |
| Validation | 27 cities/regencies | 2025      | 27           | 7         |

The training dataset has 189 observations in total. Twenty-seven (27) geographical units for 7 years, 2018-2024. Meanwhile, the validation dataset has 27 observations: 27 geographical units for one year, 2025. There are two instances of missing data: first, Bandung Barat has a missing total divorce value in 2018, and second, there is a missing value for total divorce from 2018- 2024 in Pangandaran. Bandung Barat's missing data is handled by the Multiple Imputation by Chained Equations (MICE) Method. MICE preserves relationships among variables and produces unbiased estimates under the assumption that missing data are missing at random. It is implemented through the use of IterativeImputer with Bayesian Ridge as the base estimator with 20 iterations and a tolerance of 1e-3. All six features and the target variable were included in the imputation model. The required imputation only needs to fill one value, which is the value for total divorce in Bandung Barat 2018. MICE is only applied to the training dataset to prevent data leakage from the validation set. After imputation, no missing values remained in the training data.

Pangandaran missing values are handled differently. With total divorce data missing across all training data, neither back-fill nor front-fill is possible for the total divorce value. Instead, Pangandaran is removed from the training dataset and separated from the main prediction evaluation. This problem instead offers an opportunity for this research to test the prediction evaluation which is to try it as a zero-shot case study. Pangandaran's 2025 divorce total is predicted using the model trained on the other 26 cities and regencies, with Pangandaran's 2025 input features as input. Its evaluation metrics are calculated separately from the main dataset.

**Table 2. Dataset Structure After Handling Missing Data**

| Dataset    | Units               | Period    | Observations | Variables |
|------------|---------------------|-----------|--------------|-----------|
| Training   | 26 cities/regencies | 2018-2024 | 182          | 7         |
| Validation | 27 cities/regencies | 2025      | 27           | 7         |

With the adjustment after handling missing data. The training dataset now has 182 observations in total. Twenty-six (26) geographical units for 7 years, 2018-2024. Meanwhile, the validation dataset has 27 observations: 27 geographical units for one year, 2025. A difference in the number of geographical units observed in the training data due to the removal of Pangandaran from the training dataset.

### Modeling

There are three models that will be used. These models are common effects (Pooled OLS), fixed effects, and random effects. The common effects model is used by combining time series data and cross-sectional data.

$$y = \beta_1 + \beta_2 X_2 + \beta_K X_K + \varepsilon \quad (1)$$

Coefficient  $\beta_1, \dots, \beta_K$  are typically unknown population parameters, which constitute the main parameters of interest, with  $\varepsilon$  denoting the unobserved error component [10]. Meanwhile, fixed effects are based on the assumption that the coefficient slope of each variable is constant, but the intercept varies across cross-sectional units.

$$y_{it} = X'_{it}\beta_1 + \alpha_i + u_{it}, i = 1, \dots, N; t = 1, \dots, \quad (2)$$

Where  $\alpha_i$  denotes the firm-specific intercepts, which are treated as fixed parameters to be estimated. In this specification, the global intercept term is not included in  $x_{it}$ , as its effect is absorbed by the individual fixed effects  $\alpha_i$  [10]. The last model is called the random effects model, which works by not interfering with different intercept, but rather, they are captured by error terms. This approach offers an efficiency advantage over pooled OLS by exploiting the error structure through Feasible Generalized Least Squares (FGLS), producing more precise estimates. However, it requires the strong assumption that  $\alpha_i$  is uncorrelated with the regressors.

$$y_{it} = X'_{it}\beta_1 + \alpha_i + u_{it}, i = 1, \dots, N; t = 1, \dots, \quad (3)$$

The model partitions the disturbance term into a permanent component ( $\alpha_i$ ) that is constant over time and a transitory component ( $u_{it}$ ) that varies across both individuals and time. A fundamental assumption of this approach is that both error components are orthogonal to the regressors [10]. Although equations (2) and (3) are mathematically identical, there is a distinction between the two models. The distinction lies in the assumptions regarding  $\alpha_i$ . In the fixed effects model,  $\alpha_i$  is treated as a fixed parameter and is allowed to be correlated with the regressors. However,  $\alpha_i$  is instead treated as a random component with the assumption that it is not correlated with the regressors.

### Evaluation and Deployment

In this phase, the model will be tested to determine which is better suited for prediction. The estimation procedure began with the specification and estimation of three panel data models: the Common Effects Model (CEM), the Fixed Effects Model (FEM), and the Random Effects Model (REM).

Following estimation, a series of diagnostic tests were conducted to evaluate the validity of the underlying classical assumptions for each model. A normality test is conducted. It is used to check whether the distribution is normal or not [11]. Under the null hypothesis of normally distributed residuals, the JB test statistic is distributed as Chi-square with 2 degrees of freedom. A p-value of less than 0.05 indicates that the residuals are not normally distributed. These will be conducted through the Jarque-Bera test. The Breusch-Pagan Lagrange Multiplier (LM) will test for heteroscedasticity. Of which whether the p-values are lower or higher than 0.05. A lower value means there is heteroscedasticity present. The Durbin-Watson (DW) test is for first-order autocorrelation. In this test, there are range from 0 to 4. A value of approximately 2 indicates that there is no autocorrelation, while values over 2 indicate negative autocorrelation and values below 2 indicate positive autocorrelation. Lastly, the Ramsey RESET test is used to assess linearity (functional form). This test is conducted to check for omitted variables, redundant explanatory variables, and incorrect functional form in the model [12]. The test augments the original model by adding higher-order terms of the fitted values. If the linear specification is correct, the F-statistic follows an F-distribution under the null hypothesis. A p-value below 0.05 suggests misspecification and points to possible nonlinear relationships.

To assess the predictive performance of the estimated models, this study utilizes three commonly employed forecast accuracy measures: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). As defined by Hyndman and Athanasopoulos [13]. A forecast error represents the discrepancy between the actual observation and its predicted value:

$$e_t = y_t - \hat{y}_t \quad (4)$$

Using forecast error as the basis, the evaluation metrics are calculated upon the following:

$$MAE = (1/n) \sum |y_t - \hat{y}_t| \quad (5)$$

$$RMSE = \sqrt{[(1/n) \sum (y_t - \hat{y}_t)^2]} \quad (6)$$

$$MAPE = (1/n) \sum (|y_t - \hat{y}_t| / |y_t|) \times 100\% \quad (7)$$

Where  $y_t$  is the actual observed value,  $\hat{y}_t$  is the corresponding forecast, and  $n$  denotes the total number of forecast observations. Mean Absolute Error (MAE) offers an easy-to-understand interpretation of average error magnitude, as it is presented in the same units as the dependent variable. Root Mean Squared Error (RMSE) has a particularly sensitivity to outliers, the reason behind this is that RMSE punish a larger penalty for large errors through the squaring operation prior to computing the square root. Mean Absolute Percentage Error (MAPE) provides a scale-independent, percentage-based measure that facilitates comparisons across datasets with different units or magnitudes. For all three metrics, smaller values indicate better forecast accuracy.

The model selection tests are as follows: Hausman, Chow, and Breusch-Pagan. Model selection among the three estimated models, common effects model (CEM), fixed effects model (FEM), and random effect model (REM), is guided by three specification tests. The Chow test compares CEM versus FEM, and the Hausman test compares FEM versus REM [14]. In the Hausman test, the Random Effects model is accepted if the null hypothesis ( $H_0$ ) is correct. Meanwhile the acceptance of the alternative hypothesis, hypothesis ( $H_1$ ), suggests the acceptance of the Fixed Effects model [15]. For the chow test, the null hypothesis suggests that the common effects model is appropriate, while the alternative hypothesis suggests that the fixed effects model is appropriate. Additionally, the Breusch-Pagan Lagrange Multiplier (LM) test compares CEM versus REM. For the Breusch-Pagan Lagrange Multiplier test, it essentially tests whether the variance of the individual-specific error component is zero. If it is zero, there are no random effects, and the CEM (pooled OLS) is appropriate. If the variance is greater than zero, random effects are present, making the REM a better choice. These tests were conducted to provide diagnostic information regarding the appropriate panel data structure. However, these tests were not used as the primary determinants of the final model. Instead, the selection process also considered the theoretical plausibility of each model, the interpretability of coefficient estimates, and—most importantly—the model's predictive performance as measured by MAPE, MAE, and RMSE on out-of-sample data.

This approach ensures that the chosen model is not only statistically sound but also practically useful for forecasting divorce rates. An analysis of these metrics determines whether the model achieves satisfactory performance. Should the need arise, such as unsatisfactory results. An iterative feedback loop will be implemented by repeating previous steps. This allows for recalibration and refinement of the preceding phases.

## RESULTS AND DISCUSSION

### First Prediction Model

Dataset are modeled for each of the fixed effect, common effect, and random effect. After which, the models are tested using model selection tests and predictive evaluation through MAPE, MEA, and RMSE. Model selection tests are as follows: Chow, Hausman, and Breusch-Pagan LM. In the model selection test, Hausman and Breusch-Pagan favor Random Effects, while Chow favors Fixed Effects.

**Table 3. Model Selection Summary**

| Test             | Statistics | p-value | Conclusion |
|------------------|------------|---------|------------|
| Chow             | 5.0172     | 0.0000  | FE         |
| Breusch-Pagan LM | 1899.8612  | 0.0000  | RE         |
| Hausman          | nan        | 0.0000  | RE         |

However, when using standard predictive evaluation, MAPE suggests using the Common Effects model, as it has the lowest percentage, which is 33.25%, followed by Random Effects, which is 38.07%, last with value 172.82% is fixed effect. The errors for common and random effects are 940.41 and 1034.86 units of divorces,

respectively, while fixed effects have almost four times the amount, which is 3964.87. For RMSE, it is consistent with the MAE results; common effects and random effects have similar results, while fixed effects have a significantly higher score value.

**Table 4. Model Comparison**

|      | <b>Common<br/>Effects</b> | <b>Fixed<br/>Effects</b> | <b>Random<br/>Effects</b> |
|------|---------------------------|--------------------------|---------------------------|
| MAE  | 940.41                    | 3964.87                  | 1034.86                   |
| RMSE | 1352.19                   | 4715.73                  | 1416.93                   |
| MAPE | 33.25%                    | 172.82%                  | 38.07%                    |

Following that, the classic assumption test is done. Even though the classic assumption test is not as impactful for prediction compared to causal inference, the test is still conducted to check the robustness of this model. The results are as shown in Table 3 (Classic Assumption Test). It shows that several of the tests are violated. In the normality test, all results have a p-value of 0. Which meant the rejection of the null hypothesis of normally distributed residuals. For the linearity test, the p-value is 0.0002, and the F-statistic is 14.0482. This result suggests the presence of nonlinear relationships or a possibility of omitted variables in the current specification. The autocorrelation test results show that the Common Effects Model exhibits positive autocorrelation (DW = 1.3705), the Random Effects Model displays mild positive autocorrelation (DW = 1.7298), and the Fixed Effects Model shows no evidence of autocorrelation (DW = 2.1510). The fixed-effects model passed the heteroskedasticity test with p-value > 0.05, while the others failed to pass it with p-value < 0.05.

**Table 5. Classic Assumption Test**

| <b>Test</b>        | <b>Common<br/>Effect</b> | <b>Fixed Effect</b>                     | <b>Random Effect</b>    |
|--------------------|--------------------------|-----------------------------------------|-------------------------|
| Normality          | JB=51.2309<br>p=0.0000   | JB=560.4390<br>p=0.0000                 | JB=161.6659<br>p=0.0000 |
| Heteroskedasticity | LM=22.2504<br>p=0.0011   | LM=11.0789<br>p=0.0860                  | LM=15.3757<br>p=0.0175  |
| Autocorrelation    | DW=1.3705                | DW=2.1510                               | DW=1.7298               |
| Linearity          |                          | F-statistic: 14.0482<br>p-value: 0.0002 |                         |

With these test results in mind, MAPE is still quite high for a prediction. MAPE sits above 30%, and classic assumption tests show a high degree of violation. In consideration of these, an adjustment is needed. Pangandaran, as the sole city that has no data in the training dataset, is also included in performing the forecast. This has a MAPE range of 70%- 95% across the three models. The random-effects model performs best at 73.5%, with an error value of 984.

**Table 6. Pangandaran Zero-Shot Evaluation**

| Model               | Predicted | Error | MAPE  |
|---------------------|-----------|-------|-------|
| Common Effects      | 2352      | 1012  | 75.5% |
| Fixed Effects       | 79        | 1261  | 94.1% |
| Random Effects      | 2324      | 984   | 73.5% |
| Actual 2025 Divorce |           | 1340  |       |
| Total               |           |       |       |

### Second Prediction Model

Referring to previous tests, an adjustment is needed. The first step is identifying what needs to change. The first thing in mind is linearity, as it affects predictive accuracy. The data relationship may not be in linear form, so a log transformation is performed. Log transformation is being done to data that has a large scale. It needs to be done on data that are not negative and are in percentage. With that in mind, divorce and population are data that will be log-transformed.

Each test result favors a different model. Chow indicates common effects as the more suitable option, Breusch-Pagan LM suggests random effects, and Hausman supports fixed effects. Prediction is the main goal; these different results are still sufficient and do not need major adjustment. In this context, prediction, the model is guided by predictive performance rather than a single specification test. Instead, additional tests are carried out to check for more insights.

**Table 7. Model Selection Summary (log)**

| Test             | Statistics | p-value | Conclusion |
|------------------|------------|---------|------------|
| Chow             | 1.4303     | 0.0987  | CE         |
| Breusch-Pagan LM | 4541.8932  | 0.0000  | RE         |
| Hausman          | 12.8339    | 0.0458  | FE         |

The random effects model is the best performing in terms of MAPE score, which sits at 19.95%, slightly outperforming the common effects model, which is 20.05%. A slight difference in MAE and RMSE scores between the common effects model and the random effects model. The differences are under one unit for both tests. Small, negligible differences between the two models provide evidence that the inclusion of individual-specific random effects does not materially improve forecast accuracy. Meanwhile, the fixed effects model has a substantial difference across all predictive performance tests compared to common and random effects models. This finding suggests that fixed effects model are likely sensitive to outliers and in out-of-sample prediction may not generalize well. It is also consistent with the fact that within-group variation, which fixed effects model utilize, could possibly add instability in forecasting.

**Table 8. Model Comparison (log)**

|      | Common Effects | Fixed Effects | Random Effects |
|------|----------------|---------------|----------------|
| MAE  | 1002.87        | 55039.17      | 1002.35        |
| RMSE | 1549.87        | 148896.95     | 1550.66        |
| MAPE | 20.05%         | 3709.12%      | 19.95%         |

For the classic assumption test, the normality test has shown that the residuals for all three models are not normally distributed. As shown in Table 7, the p-value for the three models has a p-value of  $< 0.05$ . In the heteroskedasticity test, none of the tests has a p-value  $< 0.05$ . This means that it passed the heteroskedasticity test. A zero autocorrelation case is the one on which the Durbin-Watson score is exactly 2.0. In this test, fixed effect has the best score, with a DW score of 2.0988. Followed by random effects with DW score of 1.855 and then common effect with DW score of 1.8233. The close proximity of the models DW score to 2.0 suggests that there is no significant autocorrelation in the model. In the final linearity test, the p-value is  $> 0.05$ . This entails that the model is linear, thereby it satisfies the linearity assumption.

**Table 9. Classic Assumption Test**

| Test               | Common Effect           | Fixed Effect                           | Random Effect           |
|--------------------|-------------------------|----------------------------------------|-------------------------|
| Normality          | JB=497.0780<br>p=0.0000 | JB=771.3316<br>p=0.0000                | JB=530.0134<br>p=0.0000 |
| Heteroskedasticity | LM=10.5246<br>p=0.1042  | LM=8.4287<br>p=0.2083                  | LM=10.3054<br>p=0.1124  |
| Autocorrelation    | DW=1.8233               | DW=2.0988                              | DW=1.855                |
| Linearity          |                         | F-statistic: 0.7318<br>p-value: 0.3923 |                         |

For the zero-shot case of Pangandaran. It performs significantly better compared to the original score as shown in Table 4. The current model after log transformation has a MAPE score of 5.3% and 5.7% for common effects model and random effects model respectively. With fixed effects trailing behind with a MAPE score of 36.1%. Compared to scores ranging from 70%-95% in the previous model, this log transformed model performs remarkably well.

**Table 10. Pangandaran Zero-Shot Evaluation (log)**

| Model          | Predicted | Error | MAPE  |
|----------------|-----------|-------|-------|
| Common Effects | 1417      | 77    | 5.7%  |
| Fixed Effects  | 1824      | 484   | 36.1% |
| Random Effects | 1410      | 70    | 5.3%  |

### Model Comparison

A comparison between the models is in order to know how they perform against one another. This step is necessary to see, it is to know whether the process that is being done to the data is suitable or unsuitable. In Table 9, the MAPE and linearity score are shown. MAPE is an intuitive measure of the prediction error percentage and linearity to know if the adjustment that has been done is appropriate. There are two improvements in the log-transformed model compared to the previous model. The common effects model and random effects model both improve by a sizeable margin, 13.20% and 18.12%, respectively. However, the fixed effects model suffers a catastrophic impact. It degrades the performance from 172.85% to 3709.12%, showing an approximately 2047% increase in errors. In the zero-shot case of Pangandaran. All the models after log transformation show an

increase in performance. The random effects model performs best at a MAPE score of 5.3%.

For the linearity test, there is a difference between the two. The original model has a p-value of 0.0002 which is under 0.05, which shows non-linearity. Meanwhile, the log-transformed model satisfies the linearity assumption with a p-value of 0.3932. Above the necessary requirement of p-value 0.05 needed for the linearity test, showing the model as being linear. These tests indicate that the log transformation is justified for this data.

**Table 11. Original and Log MAPE and Linearity Comparison**

|                             | Original     | Log      |
|-----------------------------|--------------|----------|
| MAPE Comparison             |              |          |
| Common Effects              | 33.25%       | 20.05%   |
| Fixed Effects               | 172.82%      | 3709.12% |
| Random Effects              | 38.07%       | 19.95%   |
| Pangandaran MAPE Comparison |              |          |
| Common Effects              | 75.5%        | 5.7%     |
| Fixed Effects               | 94.1%        | 36.1%    |
| Random Effects              | 73.5%        | 5.3%     |
| Linearity (RESET)           | p-value      |          |
|                             | 0.0002       | 0.3932   |
|                             | (non-linear) | (linear) |

### Supplementary Analysis

A further analysis is conducted on the model to gather more insights. The list of best-performing models for each city is captured and displayed with the corresponding MAPE score, divorce prediction, and actual divorce. There is no fixed effects model that has a best-performing model from any of the city/regency. It is between the common effects model and the random effects model. The model with the highest total number of best-performing models is the random effects model, with 16 cities/regencies, or 61.5% of city/regency. The remaining cities/regencies, totaling 10, are best performed by the Pooled OLS/common effects model, amounting to 38.5%. There are 16 cities/regencies that have MAPE under 20%, 7 cities/regencies in the 20%-50% MAPE range, and the remaining one, Indramayu, with MAPE over 50%, 52.3% to be exact.

**Table 12. List of Each City's Best-Performing Model**

| Rank | City          | Best MAPE | Best Model     | Actual | Prediction |
|------|---------------|-----------|----------------|--------|------------|
| 1    | Purwakarta    | 0.9%      | Random Effects | 2013   | 2031       |
| 2    | Kota Sukabumi | 2.0%      | Random Effects | 956    | 937        |
| 3    | Kota Banjar   | 3.9%      | Random Effects | 699    | 672        |

| Rank | City                | Best<br>MAPE | Best Model        | Actual | Prediction |
|------|---------------------|--------------|-------------------|--------|------------|
| 4    | Kota Bogor          | 5.1%         | Pooled<br>OLS     | 1597   | 1679       |
| 5    | Kuningan            | 5.4%         | Pooled<br>OLS     | 2436   | 2567       |
| 6    | Subang              | 5.5%         | Random<br>Effects | 3806   | 4015       |
| 7    | Kota Cimahi         | 5.9%         | Pooled<br>OLS     | 1080   | 1144       |
| 8    | Bekasi              | 6.1%         | Pooled<br>OLS     | 3984   | 4229       |
| 9    | Kota Bekasi         | 7.6%         | Random<br>Effects | 3798   | 3610       |
| 10   | Kota<br>Tasikmalaya | 8.5%         | Random<br>Effects | 1740   | 1592       |
| 11   | Ciamis              | 9.9%         | Random<br>Effects | 2993   | 3228       |
| 12   | Bandung Barat       | 11.8<br>%    | Random<br>Effects | 3439   | 3032       |
| 13   | Depok               | 11.8<br>%    | Random<br>Effects | 2958   | 2608       |
| 14   | Tasikmalaya         | 15.6<br>%    | Pooled<br>OLS     | 3439   | 3032       |
| 15   | Karawang            | 16.4<br>%    | Pooled<br>OLS     | 3762   | 4380       |
| 16   | Majalengka          | 17.6<br>%    | Pooled<br>OLS     | 3986   | 3283       |
| 17   | Cianjur             | 23.7<br>%    | Random<br>Effects | 4779   | 3647       |
| 18   | Kota Cirebon        | 24.8<br>%    | Random<br>Effects | 737    | 920        |
| 19   | Bogor               | 25.0<br>%    | Random<br>Effects | 6556   | 4916       |
| 20   | Sumedang            | 34.7<br>%    | Random<br>Effects | 3983   | 2601       |
| 21   | Kota Bandung        | 37.0<br>%    | Pooled<br>OLS     | 5753   | 3624       |
| 22   | Garut               | 44.8<br>%    | Random<br>Effects | 6288   | 3470       |
| 23   | Sukabumi            | 44.9<br>%    | Pooled<br>OLS     | 3098   | 4489       |
| 24   | Cirebon             | 45.0<br>%    | Random<br>Effects | 6833   | 3759       |
| 25   | Bandung             | 45.7<br>%    | Pooled<br>OLS     | 7974   | 4331       |
| 26   | Indramayu           | 52.3<br>%    | Random<br>Effects | 7894   | 3766       |

## CONCLUSION

A prediction for the total number of divorces in city/regency under West Java Province is developed. It is developed for three models: the common effects model, fixed effects model, and random effects model. Upon which the three models are evaluated to determine which model is more suitable for handling this dataset. Consisting of the total number of divorces, marriages, gender ratio, population density, population growth, and population totals (in thousands), and total average spending per month.

An initial prediction was made, which, upon further testing, showed unsatisfactory results. The best model, the common effects model, has a MAPE of 33.25% and several violations in classic assumption tests. Namely, in the context of prediction, linearity is violated. An adjustment is made, which is a log transformation for divorces and population. This process, upon further testing, shows a remarkable improvement. Reducing MAPE across all models, improving the prediction error range. The main focus on the random effects models that showed the best MAPE, 19.95%. During this process, missing data for the total number of divorces for Pangandaran in the training set was discovered. With no data to go by, this phenomenon is treated as a zero-shot study. Where in log-transformed model for the random effects model, it has a MAPE of 5.3%.

A supplementary analysis is conducted on the model and data. A discovery is found that random effects models across 16 cities/regencies in West Java Province are the best model. Meanwhile, the remaining 8 cities/regencies are best performed on common effect model. There are 16 cities/regencies that have a MAPE lower than 20%, while the remaining 8 are above 20%, with the highest reaching 52.3% as the worst-performing city/regency. For further study, an analysis could be made to discover what the common denominator is for models that have a low MAPE. Additionally, adding new data for this study can be done to add more features for testing.

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